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# GEOPHYSICAL SIGNAL RECOGNITION

LEVEL II

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## ABSTRACT

Progress of pattern recognition as applied to various geophysical signals is reviewed. They include the teleseismic signals for nuclear detection and monitoring, exploration seismic signals for oil prospecting, marine seismic signals for study of subsurface structure of ocean floor, seismic signals for earthquake prediction, seismic signals for intrusion-detection, and geomagnetic signals for study of irregularities of the earth's magnetic fields. With the exception of teleseismic signal, research in geophysical signal recognition is still in its infancy. We expect to see considerable research progress in the next decade.

# Geophysical Signal Recognition

C.H. Chen

## 1. Introduction

In recent years, computers have played an increasingly important role in geophysics especially in seismic studies such as the petroleum exploration, mineral extraction, nuclear detection, earthquake research, marine seismic profiling, and intrusion detection, etc. Computers are needed to process large volumes of seismic data from which useful information must be extracted accurately, In addition to the seismic data, geomagnetic signals are also processed by computer in large quantities. A primary function of computers has been in filtering and storage of the geophysical data while the recognition and interpretation of the filtered results is performed mainly by geophysicists or human operators. However efforts have been made by many researchers to use pattern recognition techniques in geophysical signal processing and recognition with some promising results. In this paper we shall examine the progress in geophysical signal recognition and the future directions of such research. An extensive list of references provided as bibliography at the end of the paper clearly indicates the amount of research activities in this area in the past ten years.

Pattern recognition techniques considered in this paper include preprocessing, feature or primitive selection, syntactive analysis, decision making and learning processes. Among all geophysical problems, seismic discrimination clearly can be formulated as a pattern recognition problem and has been fairly extensively studied in this context. For the exploration seismic data from which detection is made of petroleum, mineral or natural gas, pattern recognition can be used as computer-aided interpretation. Similarly for earthquake study and seismic intrusion detection, pattern recognition provides an additional dimension to problem solving. In

other geophysical signals, the need for pattern recognition is less evident. As different geophysical signals require different processing and recognition approaches, the recognition problems of various geophysical signals will be considered individually.

2. Recognition of Teleseismic Signals

Teleseismic signals are the seismic waveforms resulting from nuclear explosions and earthquakes which may originate from unknown locations. Shallow earthquakes are easily confused with nuclear explosions. Seismic networks throughout the world coupled with a prior knowledge about explosion and earthquake events have made it possible now to detect the nuclear explosion with good accuracy. Automatic pattern recognition is useful to aid or verify the human interpretation at the present stage of development. Currently available recognition results have not been close to error-free to make the automatic recognition reliable.

Mathematical feature extraction by using dynamic spectral ratio, complexity, multivariate autoregressive parameters in conjunction with the Karhunen-Loeve expansions have been considered for seismic discrimination (e.g. [6][9][19][20][31]). Features with real geophysical meaning appear to be quite important for seismic discrimination. Examples are [19],

1. Earthquakes produce approximately equal amounts of P and S waves, while explosions produce more P waves.
2. Earthquakes have relatively deep foci, while explosions have only shallow foci.
3. Earthquakes give anaseismic and kataseismic first onsets while explosions give anaseismic first onset everywhere.
4. The duration of wave trains is shorter for explosions than for earthquakes.

Unfortunately the direct application of these discriminating features

is not possible. Although explosions provide more P waves than S waves, not all earthquakes follow the average pattern. Further it is very difficult to identify particular phases for lower magnitude earthquakes. Focal depths hold a great deal of promise in discrimination. However there is still too much error associated with measurement to warrant its exclusive use. The difficulty in determining the direction of onset, due to noise, obscures the anaseismic-kataseismic discrimination feature. Again, the signal-to-noise ratio is too small, for small-amplitude events, to discriminate using the duration of the wave trains. An interesting discussion of geophysical features for nuclear detection is given by Bolt [3]. For automatic classification, the features must be computable to a good accuracy. This requires both digital signal processing and statistical techniques.

Figure 1 shows some typical seismic records which we have studied along with their Fourier amplitude spectra. The sampling rate is 10 samples/sec. with 1200 samples per record. Based on our extensive comparative study of various feature selection criteria the spectral features when accurately computed can perform the best with simple classifier. For example the high-resolution maximum entropy spectral analysis can provide more effective features than those available from the conventional modified periodogram method using fast Fourier transform. Figure 2 shows the maximum entropy spectra of two explosion and two earthquake events for a duration of 200 samples from sample number 701 to 900. For the explosion the spectral ratio defined as the ratio of signal energy above $0.5H_2$ to that below $0.5H_2$ tends to be greater than 1 while for the earthquake such ratio tends to be less than 1. The nearest neighbor decision rule is used for classification. For each pattern class, 40 seismic records are available for learning. A total of 243 seismic records which do not include learning records is for

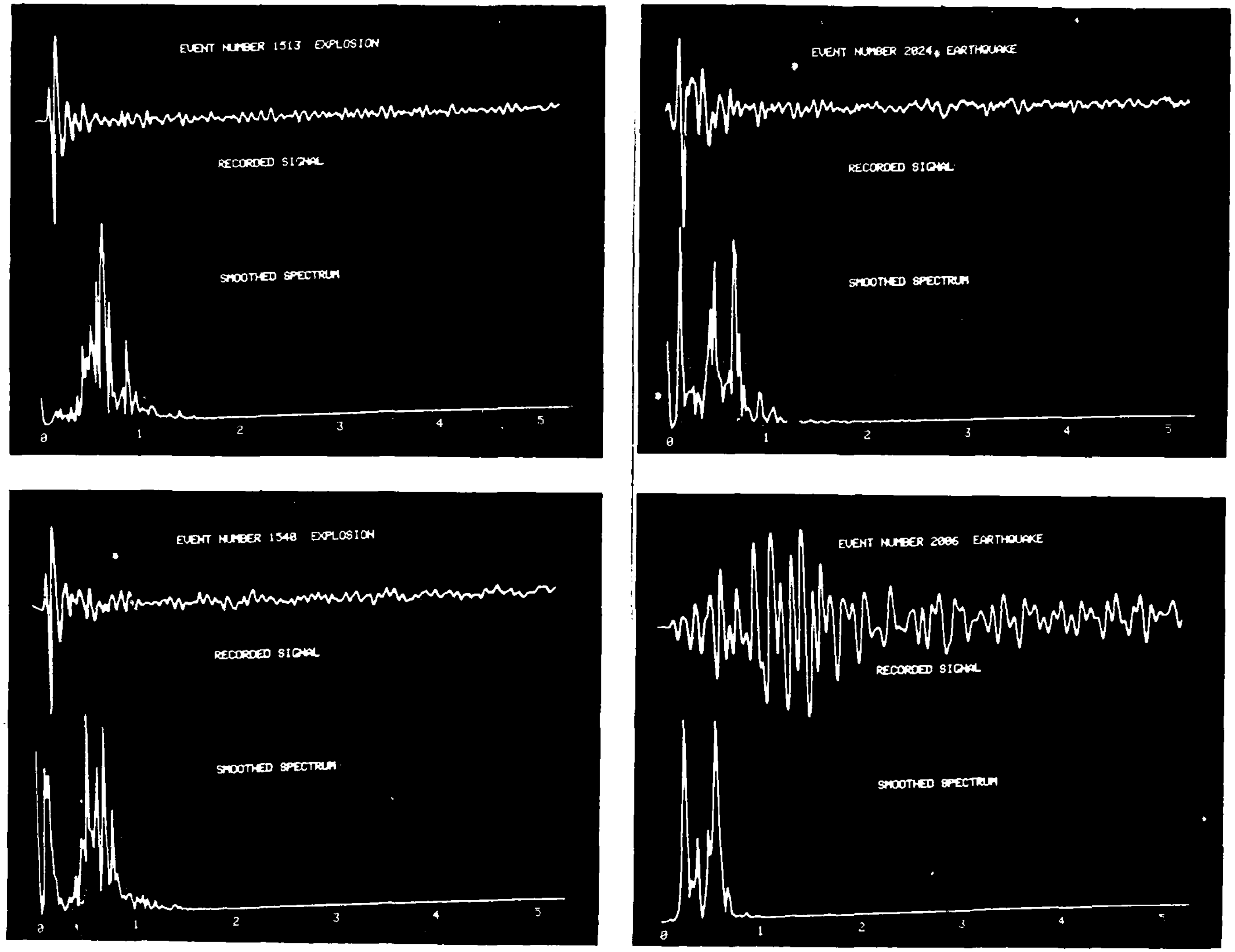


Figure 1 Typical teleseismic signals studied along with their amplitude spectra.

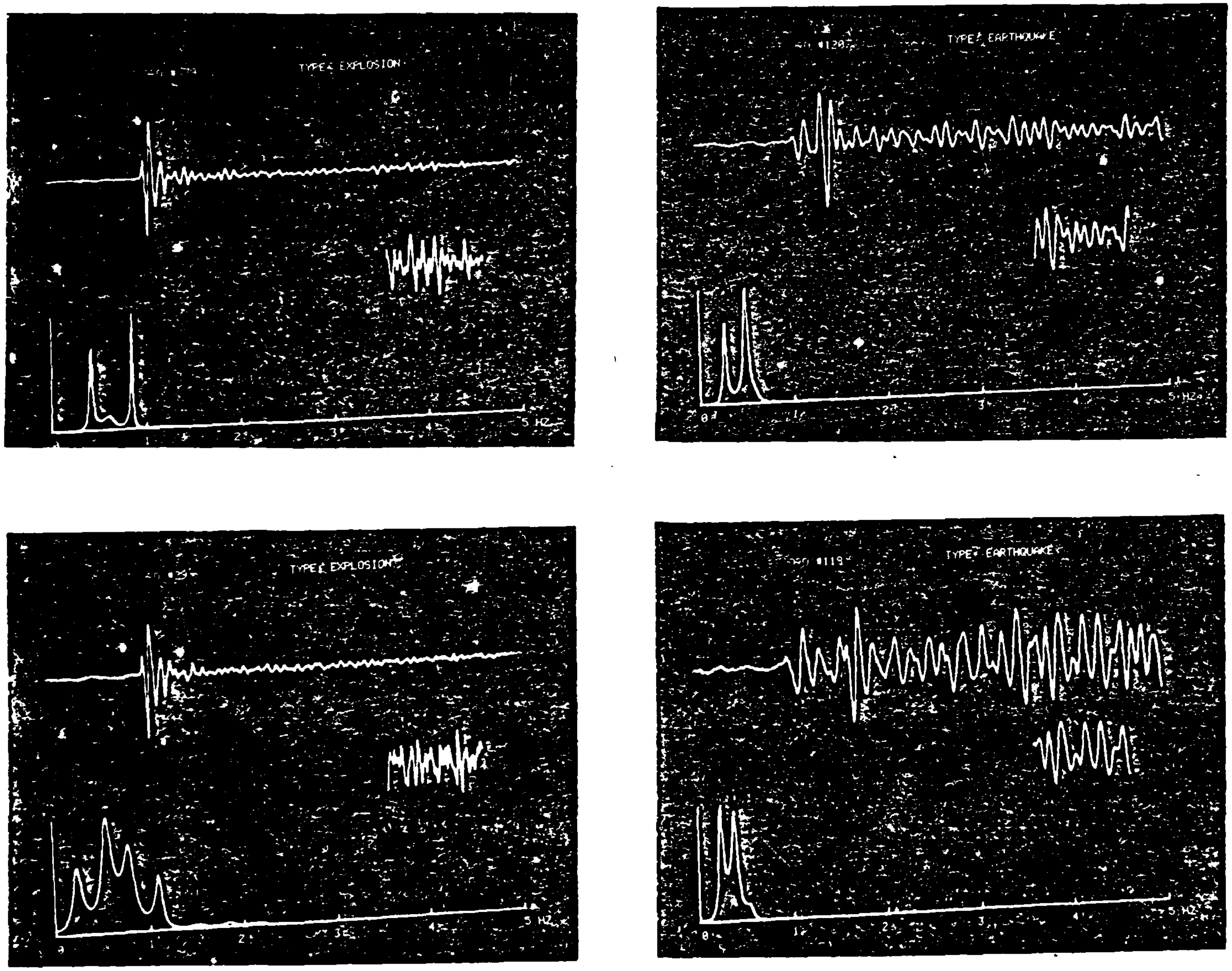


Figure 2  Maximum entropy power spectra of a 200-point section of typical teleseismic signals.

classification. Spectral ratio for 200 samples from sample number 550 to 749 and spectral ratio for 200 samples from sample number 750 to 949 are employed as two features in classification. The final classification results is 14 errors out of 243 for 94.24% correct recognition. This is the best available result with two features.

Another important feature extraction technique is the short-term spectral features. A 64-point window slides through the 1024-point seismic record generating 64 time segments with 48-point overlap between the adjacent segments. For each 64-point segment, compute the Fourier transform. The first 32 points of the Fourier transform correspond to the 5-Hz frequency interval of the seismic wave. Define $P_1$ = signal power covering the first to fifth spectral points (0 - 0.78 Hz band), $P_2$ = signal power covering the sixth to 14th spectral points (0.78 - 2.18 Hz band), and $P_3$ = signal power covering the 15th - 32nd spectral points (2.18 - 5.0 Hz band). Each $P_i$, i = 1,2,3 can be plotted as a function of time, i.e. the segment number. For each curve the ratio of the signal energies between the first 32 segments and the second 32 segments is called a short-time spectral feature. For each seismic record, there will thus be three feature values which form a vector. A set of 50 learning (training) records is taken from each class. Using the well-known Euclidean distance nearest-neighbor decision rule the best performance is around 80% correct recognition on test set. For each class, a covariance matrix $V_i$, i = 1,2 can be determined from the training set. A modified procedure is to compute the square distance

$$(x - P^{(i)})' V_i^{-1} (x - P^{(i)}) = d_i^2 \quad , \ i = 1,2 \tag{1}$$

and choose the class which provides the minimum $d_i^2$. Here $P^{(i)}$ is a nearest neighbor belonging to the ith class and x is the three-dimensional feature vector representing a seismic record. By using such weighted Euclidean distance nearest neighbor decision rule, a 94.17% correct recognition

(13 errors out of 223) is obtained. If the Bayes decision rule is used under the assumption of multivariate Gaussian density for each class, the performance is 87.92% correct recognition (27 errors out of 223). This experimental result indicates that the stationary probability assumption of the seismic record is not good. Other work on autoregressive feature extraction also based on the assumption of stationary random process for the seismic record has provided less recognition performance. The short-term spectral features described above have taken the nonstationarity into consideration.

Among other computer studies, the features based on the complex cepstial point followed by Fisher's linear discriminant gave a 94.4% correct recognition results for 36 seismic records. The autocovariance function also can provide around 89% correct recognition. The results are somewhat depending on the pre-filtering operations used. For a single discriminant, the ratio of surface wave magnitude $M_s$ to the bodywave magnitude $m_b$ is most effective for events with $m_b>4$ as the shallow earthquakes typically produce more surface waves than do explosions of equivalent energy. The combined use of statistical and structural features [7] in conjunction with an optimized decision till is a very promising approach. Syntactic method of teleseismic signal recognition has also been examined. As a highly reliable and fully automatic seismic recognition system is not likely to be available in the near future, interactive pattern recognition is more practically feasible and some important effort has been made in this direction [21].

3. Exploration and Marine Seismic Signals

In the exploration seismic study detection is made of petroleum or natural gas. In the marine seismic study, an accurate mapping is made of the subsurface geological structure of the ocean floor. Although the

purposes are quite different, the two seismic signal studies are similar. As the new petroleum deposits are much more difficult to discover on land now, exploration of petroleum deposit in the ocean floor is increasingly important and the demand for marine seismic study for oil exploration is very high. For both seismic signals, the major efforts made in the past have been in digital filtering and estimation of subsurface parameters. Pattern recognition problems can be formulated for analysis and detection of the seismic signals. In marine seismic profiling, for example, the physical parameters which describe the structure of the deep sea floors correspond to feature sets in pattern recognition. Examples of pattern classes are various rocks, sediments, mantles and oceanic layers of low, medium and high porosity. In the exploration seismic study feature extraction and decision theoretic approaches have been examined [15][16]. An important recent development is the syntactic approach [26] to segment the one-dimensional logging data, i.e. measurements of various physical rock parameters from transducers inside the borehole. The transition patterns between signal blocks are described by a set of grammatical rules.

As compared with the teleseismic signals, the exploration and marine seismic signals are much more stationary and thus both statistical and syntactic pattern analysis can be quite effective for properly formulated recognition problems.

4. Mineral Extraction and Earthquake Prediction

The use of seismics in mining exploration has been restricted so far to only some trial measurements. If seismic methods are to become popular in ore exploration, we can be sure that the signals of interest will be hidden far more "deeply" than is the case for the signals in oil prospecting. The highly developed reflection seismology that reveals subsurface structure information will be useful to mineral extraction. Pattern recognition techniques useful for petroleum exploration should also be

suitable for mineral extraction.

Computer-aided techniques have been quite helpful in earthquake prediction. However pattern recognition techniques have not been employed in earthquake study, to our knowledge; but the potential is there. For example automatic processing algorithms for microearthquake data have been examined [1], based on the syntactic structural analysis of waveforms [27][28]. There is always ambiguity associated with measuring the first arrival time from seismograms whether it is done by a seismologist or by a machine since the seismic signals are of unknown shape and are contaminated by noise. Such ambiguity can be reduced by combining the processes of picking arrivals and locating the events in an iterative fashion. A seismogram can be described as "noise followed by seismic signal", where both "noise" and "seismic signal" would have grammatical rules describing their structure. Current picking algorithms [2] use this type of structural information but in a rather ad hoc manner.

In summary, application of pattern recognition to earthquake prediction is in its infancy. Obviously various structural and geophysical information must be combined to derive a feasible algorithm for automatic prediction and interpretation.

5. Intrusion-Detection Using Seismic Sensors

One of the automatic intrusion-detection techniques is to use the seismic sensors that detect the "footstep signal" in the presence of usually strong correlated noises due to vehicle motions in the immediate vicinity. In this case the real signal is impulse-like with unknown arrival time and duration. It is necessary to employ noise cancelling algorithms such as the adaptive digital filtering and the Kalman filtering to suppress the background noise so that the footstep signal can be enhanced [10][11]. Figures 3&4 show two typical sections of seismic data containing footstep signals, along with the results of adaptive digital

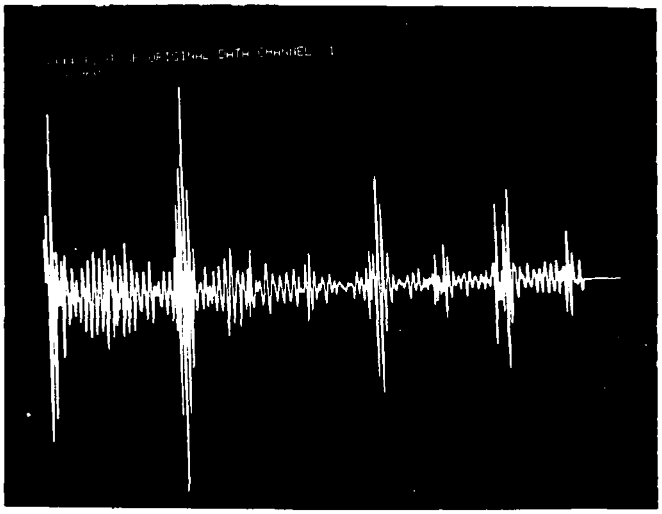

Fig. 3a One section of seismic intrusion-detection data with large signal-to -noise ratio.

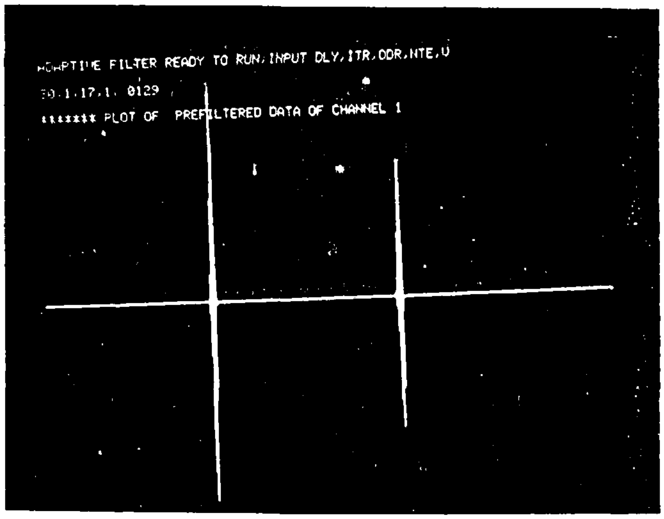


Fig. 3b Adaptive digital filtered result of Fig. 3a

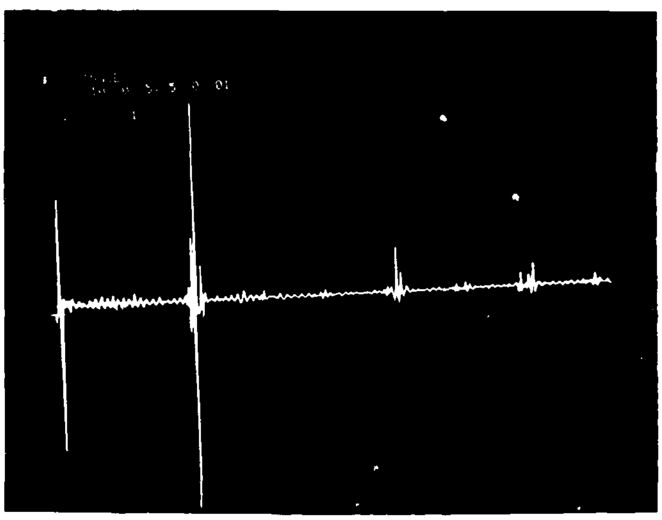

Fig. 3c Adaptive Kalman filtered result of Fig. 3a.

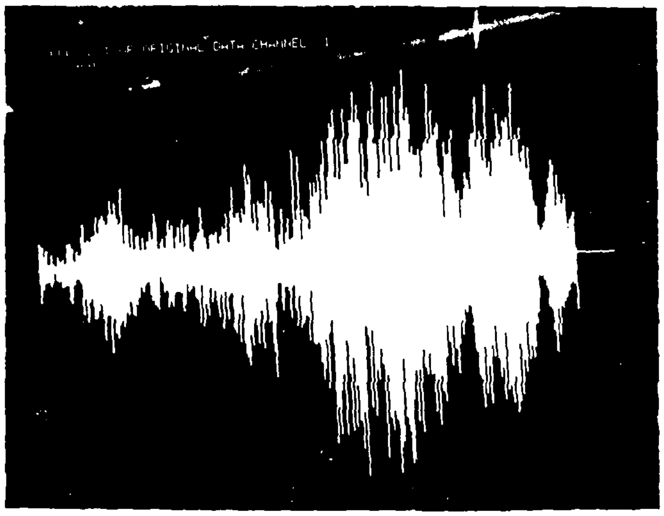


Fig. 4a One section of seismic intrusion-detection data with small signal-to -noise ratio.

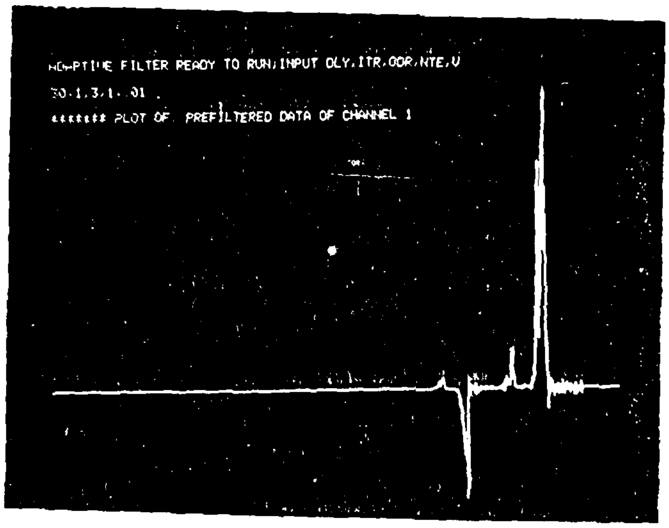


Fig. 4b Adaptive digital filtered result of Fig. 4a.

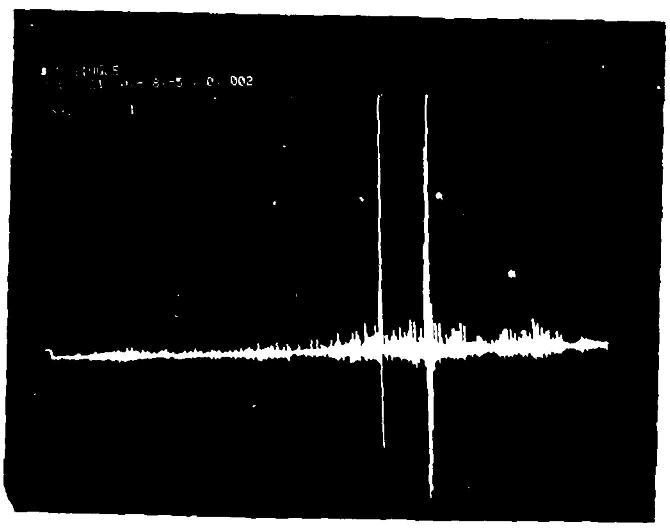

Fig. 4c Adaptive Kalman filtered result of Fig. 4a

filtering and adaptive Kalman filtering. A major portion of background noise has been removed after filtering even if the noise is very strong. Each section as shown has 960 samples at a sampling rate of 200 samples/sec. For this kind of seismic signal, spectral features are not suitable for detection. The recognition or detection problem here is to determine for each section of seismic data whether the footstep signal is present or not. The correlation detection or matched filter detection is not useful here. A simple peak detection with properly selected threshold will, however, serve the purpose. There does not appear to have any "structure" in this particular seismic signal.

6. Other Geophysical Signals

Geomagnetic signals provide some information on geophysical phenomena, which is not available from the seismic data. The spectral analysis is the main computer study that has been performed with the geomagnetic signals. An example of geomagnetic signal is the micropulsations which are often associated with structural disturbance (or storms) in the magnetosphere. Detecting a particular micropulsation event can provide a diagnosis of the properties of the magnetosphere. As the magnetosphere changes because of its varying interaction with the solar wind, the properties of the micropulsation signatures should respond . The recognition problem here is somewhat similar to the detection of machine malfunction. As a large volume of geomagnetic signals is received daily, automatic processing and recognition will certainly be an area of future research study.

Other geophysical signals include sunspot numbers, etc. As several different sensors are frequently employed in examining a particular geophysical phenomenon, how to effectively utilize information from all sources is a challenging problem in recognition study.

## 7. Conclusion

As compared with recognition of speech and biomedical signals, progress in geophysical signal recognition is much slower. There are many promising areas of research as described in this paper. Suggested future approaches are the following:

(1) Understanding the geophysical phenomenon is essential as different geophysical signals may require quite different recognition approaches.

(2) Signal processing is an integral part of signal recognition as a number of distinct properties can only be derived after extensive signal processing.

(3) Fully automatic recognition may not be a realistic goal. Some human interaction may be necessary to complete the recognition task.

(4) Information from various geophysical sensors should be integrated and utilized to arrive at the best recognition result.

## Bibliography


1. K. R. Anderson, "Automatic analysis of microearthquake network data," Geoexploration Journal, vol. 16, pp. 159-175, 1978.

2. K. R. Anderson, "Automatic processing of local earthquake data," Ph.D. thesis, Department of Earth and Planetary Sciences, M.I.T., August, 1978.

3. B. A. Bolt, "Nuclear Explosions and Earthquakes - The Parted Veil," Freeman, San Francisco, CA, 1976.

4. R. D. Bouvier, "Seismic pattern recognition," unplished master thesis, Air Force Institute of Technology, December, 1972; AD757877.

5. C. H. Chen,"Application of pattern recognition techniques to oceanographic signal processing," IEEE International Conference Proceedings on Engineering in the Ocean Environment, Panama City, FL, pp. 164-166, September, 1970.

6. C. H. Chen, "Feature extraction and computational complexity in seismological pattern recognition," Proceedings of the Second International Joint Conference on Pattern Recognition, Copenhagen, Denmark, 1974.

7. C. H. Chen, "On statistical and structural feature extraction," in "Pattern Recognition and Artificial Intelligence," edited by C. H. Chen, Academic Press, New York, NY , 1976.

8. C. H. Chen, "Comparison of seismic features extracted by digital signal processing techniques," Proc. of IEEE International Conference on Acoustic, Speech and Signal Processing, Hartford, CT, pp. 148-150, 1977.

9. C. H. Chen, "Seismic pattern recognition," Geoexploration Journal, vol. 16, pp. 133-146, 1978.

10. C. H. Chen, "Note on Kalman filtering for seismic signal detection," Technical Report SMU-EE-TR-80-1, February, 1980.

11. C. H. Chen, "Adaptive and learning algorithms for intrusion-detection with seismic sensor data," presented at the Workshop on Digital Signal and Waveform Analysis, Miami Beach, FL, December, 1980.

12. C. H. Chen, "Digital Waveform Processing and Recognition," CRC Press, 1981, Chapter 7&8.

13. C. H. Chen, "Application of pattern recognition to seismic wave interpretation," Chapter 5 of the "Applications of Pattern Recognition," edited by K. S. Fu, CRC Press, Inc., 1981.

14. O. Dahlman and H. Israelson, "Monitoring Underground Nuclear Explosions," Elsevier, Amsterdam, 1977.

15. R. J. P. de Figueiredo, co-editor, "Concepts and Techniques in Oil and Gas Exploration" to be published by Society for Exploration Geophysicists.

16. R. J. P. deFigueiredo, special issue guest co-editor on "Pattern Recognition as Applied to Petroleum and Gas Exploration," IEEE Trans. on Geoscience and Remote Sensing,to be published.

17. K. S. Fu, editor, "Syntactic Pattern Recognition Applications," Springer-Verlag, New York, NY, 1977.

18. H. Israelson, "Short-period identification," in "Exploitation of Seismograph Networks," edited by K. G. Beauchamp, NATO ASI Series E, Applied Sciences No. 11, Noordhoff, Leiden, 1975.

19. R. B. Ives, "Feature and decision function selection for the detection of nuclear detonations from seismic signatures," Conference Record of 1976 Joint Workshop on Pattern Recognition and Artificial Intelligence, pp. 148-154.

20. R. B. Ives, "Dynamic spectral ratios with variable frequency bands as seismic discriminants," Proc. of the International Symposium on Computer-Aided Seismic Analysis and Discrimination, June, 1977.

21. R. B. Ives, "PAL, a highly tutorial interactive pattern recognition program for seismic analysis," Proc. of the International Symposium on Computer-Aided Seismic Analysis and Discrimination, June, 1977.

22. J. Lin, Unpublished report on syntactic methods for seismic classification, Advanced Automation Research Lab., Purdue University, 1977.

23. A. N. Mucciardi, Unpublished report on seismic classifiers, 1972.

24. C. S. Sarna and H. Stark, "Pattern recognition of waveforms using modern spectral estimation technique and its application to earthquake/explosion data," Proc. of 5th International Conference on Pattern Recognition, pp. 8-10, Miami Beach, FL, December, 1980.

25. R. H. Schumway and A. N. Unger, "Linear discriminant functions for stationary time series," Journal of American Statistical Association, vol. 67, pp. 948-956, 1974.

26. H. E. Stephanou, "A syntactic approach to well log segmentation," presented at the Workshop on Digital Signal and Waveform Analysis, Miami Beach, FL, December, 1980.

27. G. Stockman, L. N. Kanal, and M. C. Kyle, "Structural pattern recognition of cartoid pulse waves using a general waveform parsing system, Communication of ACM, vol. 19, pp. 688-695, 1976.

28. G. Stockman, "A problem - reduction approach to the linguistic analysis of waveforms," Technical Report No. 538, Computer Science Department, University of Maryland, College Park, Maryland, 1977.

29. D. Tjøstheim, "Recognition of waveforms using autoregressive feature extraction," IEEE Trans. on Computers, vol. C-26, pp. 268-270, 1977.

30. D. Tjøstheim, "Improved seismic discrimination using pattern recognition," Physics of Earth and Planetary Interiors, vol. 16, pp. 85-108, 1978.

31. D. Tjøstheim and O. Sandvin, "Multivariate autoregressive feature extraction and the recognition of multichannel waveforms, IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. PAMI-1, no. 1, pp. 80-86, January, 1979.

32. W. R. Youngblood, "Seismic discrimination by a one-dimensional harmonic analysis," unpublished master thesis, Air Force Institute of Technology February, 1972.

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